Multi-Objective Scheduling Optimization for Mobile Energy Supplemented Micro-Grid

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Abstract. Microgrid scheduling optimization is a complex optimization problem, existing research work is mainly focused on the energy scheduling optimization and the economic benefit scheduling optimization. This paper makes use of mobile charging equipment to provide supplement energy for microgrid with insufficient energy supply, and study the electric load sequence scheduling optimization problem. A multi-objective scheduling optimization model is built by comprehensively considering the benefit from staggered peak energy storage, equipment cost, charging cost and punishment cost caused by delayed charging, and a novel particle swarm optimization algorithm is proposed to maximize the economic benefit of the microgrid. Extensive experiments verify the efficiency of the proposed algorithm, and analyze the impacts of different parameters on the economic benefit.

Keywords: Multi-objective optimization, microgrid, scheduling optimization, mobile energy supplement

1. INTRODUCTION

With the development of national economy, the forms of electricity consumption are more and more diversified. It is urgent to adjust the energy structure, develop low-carbon economy, fully develop and utilize renewable energy, promote the energy revolution and take the road of sustainable development [1]. Microgrid is a small power generation, transmission and distribution system composed of distributed power source, distributed energy storage, power electronic energy conversion device, load and protection device, etc. With the further application of microgrid, how to effectively dispatch and manage distributed energy in microgrid to maximize economic and social benefits has become an important research direction. Microgrid shoulders the important mission of promoting the structural reform of the energy supply side and improving the intelligence level of the energy system, but due to the complexity of energy types and application environment, there are certain challenges to the overall optimization of the microgrid system [2-3].

The optimization problem of microgrid is to improve the economic benefit as much as possible under various constraints. How to improve the power quality and how to ensure reliable power supply are also the technical difficulties to be overcome by the current microgrid. A large number of complex optimization techniques, such as adaptive dynamic programming [4], nonlinear programming [5] and sequential quadratic programming [6], have been used to solve the control optimization problem of microgrid systems. In [7], the management model of operating cost and reliability of distributed generation system is established, and the improved ant colony algorithm is adopted to solve the objective function. In [8], in order to maximize the generating capacity of the microgrid, all transmission lines are effectively managed. Considering the power loss of transmission lines, the ADP algorithm is used to optimize the total operation and maintenance cost of microgrid. In [9], a model of dynamic multi-objective optimal dispatch is constructed to minimize the operational and environmental costs of microgrid. In [10], microgrid is summarized as a multi-objective optimization problem with nonlinear constraints, which minimizes the operation cost of the system on the premise of meeting user needs and system security.

This paper will focus on the problem of maximizing economic benefits with mobile energy supplement in microgrid, based on the background of insufficient energy supplement and the energy harvesting ability in public grid and Microgrid respectively. The multi-objective optimization scheduling model of microgrid is constructed by comprehensively considering the benefit from staggered peak energy storage, equipment cost, charging cost and punishment cost caused by delayed charging. To address this problem, we propose a multi-objective optimization scheduling scheme based on heuristic algorithm with mobile charging device, that is, the mobile charging device carries a fully charged battery to charge the electric load in microgrid, control the charging sequence to optimize multiple objectives, and maximize the economic benefits for the microgrid.

2. MICROGRID MODEL

2.1. Microgrid system module

This system is a small microgrid system. The energy collection unit in the system is mainly solar energy collection to simplify the calculation, and the solar panels are installed in each electric load. The number of electric loads is N. This system has the monitoring capability of grid connection and Island, and the specific distribution is shown in Fig. 1. In this scenario, the microgrid is in an Islanded State because the system cannot be powered by its peak power supply and its Standby Generator are out of order, the main energy comes from solar energy.

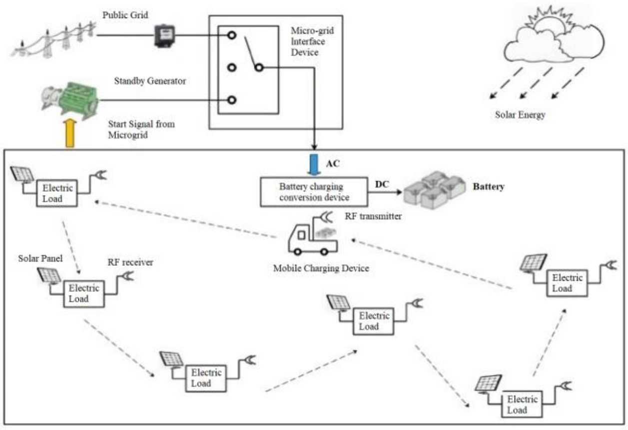

Fig.1 Microgrid System

2.2. Model of Solar Energy Harvesting

The ability to harvest solar energy is affected by the outside factors, mainly including: the intensity of sunlight and the working temperature of solar panels. According to the intensity of light and ambient temperature, combined with the output characteristics of solar panels, the output capacity of solar panels can be calculated. The output power of solar panels in the system is as follows [11]:

$$P_{PV} = P_{STC}\frac{G_{AC}}{G_{STC}}\left[1+K(T_c-T_r)\right] \quad (1)$$

$$T_C = T_{amd} + 0.0138\times(1+0.0138T_{amd})\times(1-0.042V)\times G_{AC} \quad (2)$$

where STC represents standardized experimental conditions: solar radiation intensity is 1000 W/m^2, and ambient temperature is set at 25℃. P_{STC} is the maximum power under STC. G_{AC} is the actual light intensity. G_{STC} is the light intensity of 1000 W/m^2 under STC. K is the power temperature coefficient, and the value is 0.27%/°C. T_C is the working temperature of solar panels. T_r is set at 25°C, indicating the reference temperature. T_{amd} is the ambient temperature. V is the wind speed of the environment. In this work, the energy collected by different electric loads is different due to the insufficient solar energy supplement capacity and the different distribution positions of electric loads. According to (1) and (2), and combined with different load positions, the energy stored in each load battery at this time is calculated, and they are respectively stored in the set: $E_{se}^0 = \left\{e_{se}^0(1), e_{se}^0(2), ..., e_{se}^0(i), ..., e_{se}^0(N)\right\}$.

In this system, mobile charging device (MCD) is constructed by means of mobile device carrying wireless energy transmission system. The energy transmission efficiency is defined as P_c, and the empirical wireless charging model is shown in (3)

$$P_c = \frac{G_s G_r \eta}{L_p}\left(\frac{\lambda}{4\pi(d_{ms}+\beta)}\right)^2 P_0 \quad (3),$$

where d_{ms} represents the distance between the electric load and the MCD, P_0 is the output power, G_s is the gain of the source antenna which is equipped on the MCD, G_r is the gain of the receive antenna, L_p and λ denote the rectifier efficiency and the parameter to adjust the *Friis'* free space equation for short distance transmission, respectively.

Since the MCD moves to the position near the electric loads, the distance can be regarded as a constant. To highlight the impact of different charging power on the charging performance, (3) can be simplified to (4)

$$P_c = \frac{\Delta}{\mu}\cdot P_0 \quad (4)$$

where $\Delta = G_s G_r \eta \lambda^2 / 16\pi^2 L_p$, $\mu = (d_{ms}+\beta)^2$. The moving speed of the MCD is set as v_{ms}.

2.3. Models of Charging energy consumption and MCD mobility

Before analyzing the energy consumption model, the following assumptions need to be made: Assuming that the microgrid is in a closed area of L×L, the electric loads can detect its own information, including location, residual energy, different energy consumption rates and maximum energy reserves. Different power loads have different energy consumption rates due to different tasks, but have the same maximum energy reserves. In addition, the electric loads can transmit their own information to the MCD via the antennas. MCD can realize the scheduling of charging tasks in the microgrid due to its maximum energy storage $E_{\max}^{mc}$ and sufficient computing capacity.

The position of each electric load is defined as el_i, $el_i = (x_i, y_i)$, $i \in (1, N)$, The distance between different loads is $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$, $i \neq j$, $i, j \in [1, N]$. Before each electric load is charged by MCD for the microgrid, the initial residual energy is stored by solar energy, so the initial residual energy of each load is set as $E_{el}{}^0$, and $E_{el}{}^0 = E_{se}{}^0$.

Unit energy consumption rate is set as ξ because different electricity loads have different jobs, and the energy levels are set as $ECL = (ecl_1, ecl_2, ..., ecl_N)$, according to the different works, and the energy consumption rates of different loads are defined as $el_c(i) = ecl_i \times \xi$, $i \in N$. To achieve better economic benefit, the charging sequence of Microgrid will be optimized, and the initial sequence of electric load will be reordered. Therefore, we define the charging sequence as $\Pi = \{el_1, el_2, \ldots, el_k, \ldots, el_N\}$, where el_k represents the *k*-th electric load to be charged. Build the following function mapping relationship for the initial and reordered numbers of electric loads in mathematically, which is $k = g(i), i, k \in [1, N]$. Furthermore, we define the number of exhausted loads as n_{TD}, and its downtime is defined as $td_{el}(i) = e_{el}{}^{0}(i) / elc(i)$, $i \in [1, N]$.

During the charging process, MCD will charge the loads in the microgrid one-to-one according to the optimized charging sequence Π'. There are two main objects of study in the charging process: one is the charging quantity, the other is the moving distance. The energy loss caused by these two parts has an impact on the economic benefits of the whole system. The total amount of charging and the total movement distance in the energy consumption process are analyzed respectively. The time for MCD to reach the *k*-th load to be charged is defined as $t_r(k)$, which mainly consists of two parts, one is the moving time $t_m(k)$, and the other is $\sum_{j=1}^{k-1} t_c(j)$, the total time to charge the previous *k*-1 nodes. The moving time $t_m(k) = L(k) / v_{ms}$, in which, $L(k)$ represents the distance to the *k*-th load, $L(k) = L(k-1) + d_{k,k-1}$, and $d_{k,k-1}$ represents the distance from the *k*-1-th point to the *k*-th point (assuming the initial position of MCD is (0,0)). Charging duration of the *k*-th load is $t_c(k) = (E_{\max}^{d} - e_{el}(k)) / P_c$. $E_{\max}^{d}$ is the maximum energy capacity of the electric load, and $e_i(k)$ is the residual energy of the *k*-th load, when $e_{el}(k) > 0$, $e_{el}(k) = e_{el}{}^{0}(i) - el_c(i) \times t_r(k)$, else $e_{el}(k) = 0$. Therefore, the charging demand of each load in the system is $E_{\max}^{d} - e_{se}^{0}(i)$, and the total charging demand is $\sum_{i=1}^{N}\left(E_{\max}^{d} - e_{se}^{0}(i)\right)$. During the charging process, the total movement distance is L^T, $L^T = \sum_{i=1}^{N} d_{i,i-1}$, where $d_{0,1}$ is the distance from (0,0) to the position of the first charged load.

3. The Formulation of Multi-objective Optimization Scheduling Problem

The economic benefits of microgrid mainly consider the economic benefits and the expenditure costs. The economic benefits include the energy harvested and stored by solar energy and staggered peak energy storage of batteries. Expenditure costs include cost of equipment, charging and punishment, which are shown below.

3.1. The economic benefit of microgrid

This paper sets the total economic benefit as f_g, the economic benefit from solar energy as R_{es}, the economic benefit from staggered peak energy storage of battery as R_c. And the economic benefit from per unit of solar energy is set as r_s, the peak and bottom electricity price is set as r_p and r_v respectively.

The set of energy stored by solar energy collection for each load is $E_{se}^{0} = \left\{e_{se}^{0}(1), e_{se}^{0}(2), ..., e_{se}^{0}(i), ..., e_{se}^{0}(N)\right\}$. Therefore, the total energy harvested by solar energy collection is (5)

$$E_{se}^{T} = \sum_{i=1}^{N} e_{se}^{0}(i) \tag{5}$$

and the economic benefit from solar energy is (6)

$$R_{es} = r_s \times E_{se}^{T} \tag{6}$$

The economic benefit from staggered peak energy storage of battery is (7)

$$R_c = (r_p - r_v) \times E_{\max}^{mc} \tag{7}$$

The total economic benefit is (8)

$$f_g = R_{es} + R_c \tag{8}$$

3.2. Charging Cost

According to Section 2.4, the total charging demand of all electrical equipment is $\sum_{i=1}^{N}\left(E_{\max}^{d} - e_{se}^{0}(i)\right)$, the benefit loss index caused by unit energy of charging in the process of charging is set as p_c, the total moving distance of the charging task is L^T, the energy consumed by moving MCD unit distance is em_{mcd}, the benefit loss index caused by the movement process is set as p_m. Therefore, the cost of the charging process is (9)

$$f_c = p_c \times \sum_{i=1}^{N}\left(E_{\max}^{d} - e_{se}^{0}(i)\right) + p_m \times L^T \times em_{mcd} \tag{9}$$

3.3. Cost of Equipment

The cost of solar energy equipment and mobile charging equipment is E_{sc} and E_{mcd} respectively. Standardize the problem, and define the service life times of different equipment as n_{sc} and n_{mcd} respectively. Therefore, the cost of charging equipment and solar equipment in each charging process is (10)

$$f_{ec} = \frac{E_{mcd}}{n_{mcd}} + \frac{E_{sc}}{n_{sc}} \tag{10}$$

3.4. Punishment Cost

In the process of charging, if the loads cannot be timely charged, it will affect the work of the microgrid, which will have an impact on the benefit of the system. This paper sets the punishment factor as p_{TD} to standardize the costs, and sets the punishment cost caused by the energy depletion of the equipment as (11)

$$f_p = p_{TD} \times n_{TD} \tag{11}$$

3.5. Constraints

The energy storage capacity of MCD and the maximum energy storage of electric loads impose constraints on the charging process, and the constraints are as follows:

1) Electrical equipment cannot be overcharged, so

$$e_{se}^{0}(i) \le E_{\max}^{d}, \; i \in [1, N] \tag{12}$$

2) The total charging amount cannot exceed the maximum energy storage of MCD, so

$$\sum_{i=1}^{N}\left(E_{\max}^{d} - e_{se}^{0}(i)\right) + L^T \times em_{mcd} < E_{\max}^{mc} \tag{13}$$

3.6. Multi-objective optimization scheduling problem formulation

To sum up, the total benefit of microgrid should be the total economic benefit minus all related costs during the charging process, which is as follows

$$f_T = f_g - f_c - f_{ec} - f_p \tag{14}$$

In addition, (14) is restricted by two constraints. Therefore, the multi-objective optimization scheduling (MOS) problem can be expressed as (15):

$$\begin{aligned} &Maxmize: f_T(\Pi) \\ &s.t.\ \ (11)\,(12) \end{aligned} \tag{15}$$

4. Particle Swarm Optimization Approach for Multi-objective Optimization Scheduling in Microgrid

In this paper, we design a particle swarm optimization approach for multi-objective optimization scheduling (PMOS) problem. The algorithm mainly optimizes MCD's load charging sequence in the microgrid to maximize the economic benefits of the system. We normalize the MOS problem, and use the charging sequence Π as the algorithm for the i-th optimization particle X_i, which will use the total benefit $f_T(\Pi)$ of the microgrid as the algorithm's fitness function $Fitness(X_i)$. Therefore, (14) can be converted to (16)

$$\begin{aligned} &Maxmize: Fitness(X_i) \\ &s.t.\ \ (11)\,(12) \end{aligned} \tag{16}$$

The best position experienced by the i-th particle is called the best historical position, which is recorded as $P_i = (p_{i1}, p_{i2},..., p_{iN})$. The corresponding fitness value F_i is the best fitness value of individual. At the same time, each particle also has its own change speed $V_i = (v_{i1}, v_{i2},..., v_{iN})$. The best position experienced by all particles is called the best position in global history, which is recorded as $Pg = (Pg_1, Pg_2,..., Pg_N)$, and the corresponding fitness value is the best fitness value in global history. In this algorithm, for the n-th generation particles, the change speed and position update iteration of the j-th dimension $1 \le j \le N$ are as follows:

$$v_{ij}^{n+1} = \omega \times v_{ij}^n + c_1 \times r_1 \times (p_{ij}^n - X_{ij}^n) + c_2 \times r_2 \times (p_{gj}^n - X_{ij}^n) \tag{17}$$

$$X_{ij}^{n+1} = X_{ij}^n + v_{ij}^n \tag{18}$$

Algorithm 1: Particle swarm optimization approach for multi-objective scheduling optimization

1: Generate initial Particle swarm, the number of particles is m;
2: **for** each particle i **Do**
  Initialize position X_i and velocity V_i for particle i in N-dimensional problem space;
3: **end**
4: set termination = false;
5: **while** termination = false **do**
6: **for** $i = 1; i \le N; i++$ **Do**
7: Compute the fitness value of particle i according to (15);
8: Update the historical best position P_i of particles i;
9: **end**
10: Update the global best position Pg of Particle swarm;
11: **for** $i = 1; i \le m; i++$ **Do**
12: Update the speed of particle i according to (17);
13: Update the position of particle i according to (18);
14: Calculate the fitness of particle i with $Fitness(X_i)$
15: **end**
16: **if** $Fitness(X_i)$ is the minimum
17: termination = true;
18: **else**
19: repeat step 5-16;
  end if
20: **end**
21: Output the global best solution and the corresponding position of particle i;

where ω is inertia weight, c_1 and c_2 are normal numbers called acceleration coefficients, r_1 and r_2 are two random numbers that vary in the range of [0,1]. The process of the algorithm is described in Algorithm1.

The global best solution output from PMOS algorithm is the maximum global economic benefit of microgrid, and the corresponding position of particle i is the best charging sequence of MCD.

5. Performance Evaluation

We conducted simulation tests to evaluate the performance of our proposed PMOS algorithm with Matlab2020a. To highlight the superiority of our proposed algorithm, we take the Genetic Algorithm and greedy algorithm as the baseline algorithms. Based on these two algorithms, we propose genetic algorithm approach for multi-objective optimization scheduling (GAMOS) problem and greedy strategy approach for multi-objective optimization scheduling (GSMOS) problem respectively, where the greedy strategy is to determine the charging sequence according to the priority of the load downtime. The crossover factor and mutation factor of GA algorithm are set as 0.8 and 0.1 respectively. In addition, ω is set as 1 and the other parameters used in this experiment are shown in Table 1, and the transmission efficiency of wireless power transmission is 50%.

Table 1 Initial Setting of Parameters

Symbol	Value
$E_{\max}^{mc}$	5000
$E_{\max}^{d}$	30
$\frac{E_{mcd}}{n_{mcd}}$	70
$\frac{E_{sc}}{n_{sc}}$	60
r_s	6
r_p	0.7
r_v	0.3
p_c	6
p_m	2
p_{TD}	100
P_c	6
v_m	3

Then, the impact of number of electric loads, the charging speed of MCD and moving speed of MCD on global benefit of microgrid, moving distance and energy exhausted load are described as below.

5.1. Impact of number of electric loads

In this section, we first evaluate the impact on microgrid via varying the number of electric loads. As shown in Fig.2, as the amount of electricity load continues to increase, the benefit also continues to rise. This point highlights that during the mobile charging process, the benefits of initial solar storage are greater than the losses during the charging and moving processes, which is the reason why the benefit continues to rise. The Fig.3 shows that with the increase of loads, the moving distance increases significantly. This happens because as loads increase, mobile charging units need to move more distances in order to charge them.

Similarly, as shown in the Fig.4, the number of loads running out of energy also goes up. The reason for this phenomenon is that under the premise of the same energy replenishment ability and moving speed, the more loads, the more the demand for charging. MCD needs to spend more time to charge the previous load, which will lead to the failure of subsequent load to be charged in time, resulting in energy depletion. However, it is obvious that under the same charging capacity, the PMOS algorithm has higher economic benefits compared to other algorithms, with shorter moving distance and a smaller number of energy exhausted loads, which proves the superiority of PMOS algorithm.

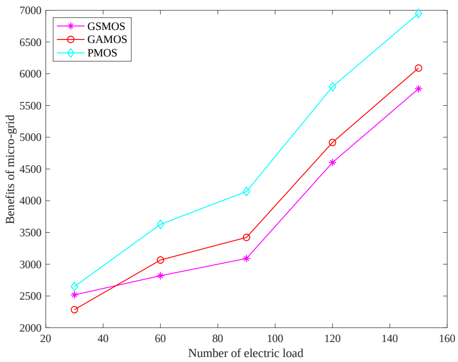

Fig. 2 Economic benefit changes with number of electric loads.

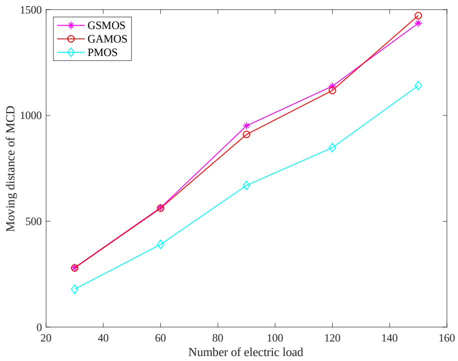

Fig. 3 Moving distance changes with number of electric loads.

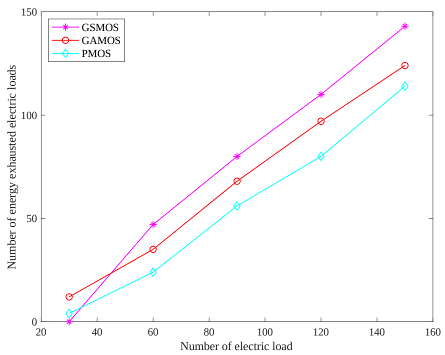

Fig. 4 Number of energy exhausted loads changes with number of electric loads.

5.2. Impact of charging speed of MCD

It can be seen from Fig. 5 and Fig. 7, with the increase of maximum capacity of load, the change trend of the economic benefit of microgrid and the number of exhausted loads is opposite while varying the charging speed of MCD. This is because as the charging speed increases, the charging time will be shorter, which will allow the MCD to have more time to charge the energy critical loads, which will reduce the number of energy exhausted loads and the penalty costs will also be reduced, resulting in higher economic benefits.

As the aspect of moving distance of MCD, the moving distance fluctuates slightly with the change of charging speed, and the PMOS algorithm has the smallest moving distance and the smallest fluctuation.

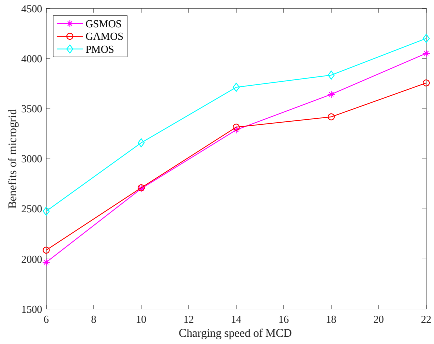

Fig. 5 Economic benefit changes with the charging speed.

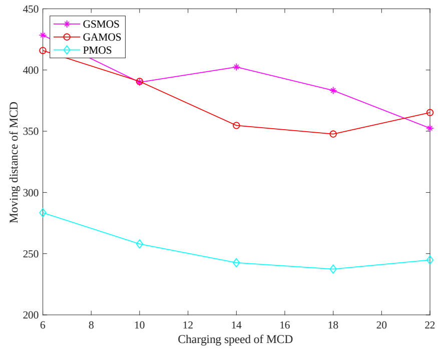

Fig. 6 Moving distance changes with the charging speed.

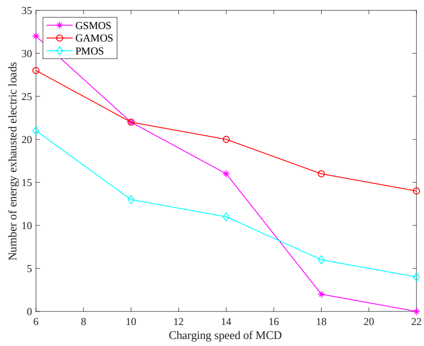

Fig. 7 Number of exhausted loads changes with the charging speed.

5.3. Impact of moving speed of MCD

As shown in Fig. 8, economic benefits continue to rise as the moving speed of MCD increases, because the higher moving speed allows MCD to move to the energy critical loads more quickly, reduces the penalty costs, and increases economic benefits. It is clearly that the growth rate slows down significantly after the moving speed reaches 3, which highlights that the effect of the moving speed on economic benefit is relatively small.

From Fig. 9 it can be seen that the moving distance is mainly affected by the randomness of the position of loads, so its variation rule is still fluctuating within a certain range, and the moving distance and fluctuation range of PMOS algorithm are the smallest. Furthermore, the change rule in Fig. 10 is similar to Fig. 7 for similar reasons.

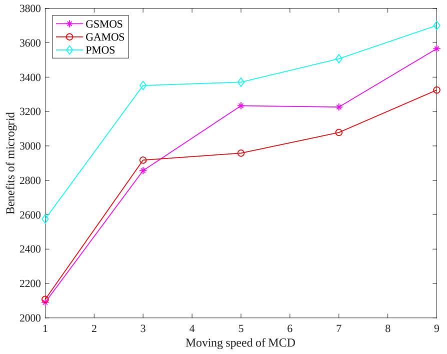

Fig. 8 Economic benefit changes with the moving speed.

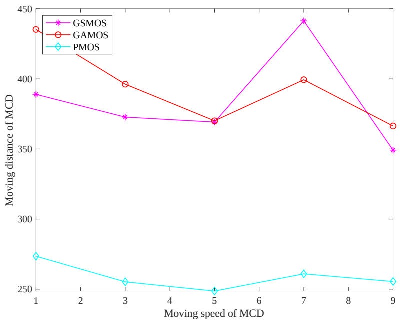

Fig. 9 Moving distance changes with the moving speed.

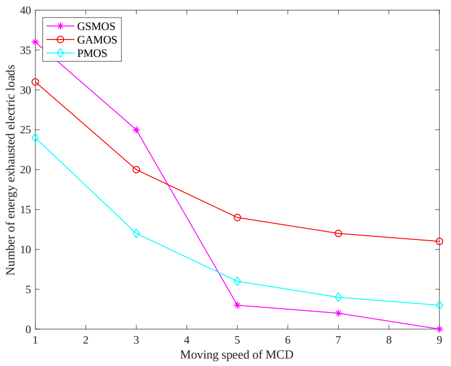

Fig. 10 Number of exhausted loads changes with the moving speed.

6. Conclusion

In this paper, when the external energy replenishment ability is insufficient, the mobile energy replenishment is introduced to optimize the scheduling of mobile charging device to realize the multi-objective optimization scheduling of microgrid. Under the condition of satisfying the system constraint and model constraint, the multi-objective optimization scheduling model of system benefit and multi-cost expenditure is established. To address the above problem, we propose a particle swarm optimization approach for multi-objective optimization scheduling. The impact of number of electric loads, the maximum energy capacity of electric load, the charging speed of MCD and moving speed of MCD on global benefit of microgrid, moving distance and energy exhausted load have been analyzed. The results show that the proposed algorithm can obtain higher economic benefits compared with other algorithms when the experimental parameters are changed, which provides a feasible scheduling scheme for the research scenario where mobile energy supplement is introduced due to the lack of power supply capacity of the microgrid due to unexpected situations. The scheduling optimization method of mobile energy supplement based on multi-objective optimization for microgrid has important practical significance for the future research of the scheduling problem of microgrid.

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